Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

Predicting Entrepreneurial Success in the Digital Economy Using Machine Learning Techniques

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Abstract –The features of intelligent entrepreneurship as it becomes a social phenomenon in national economies and the effects of this phenomenon on the economy are explored in this paper. There is evidence that the environment of modern entrepreneurship is associated with intellectual, informative, and creative pursuits. Redefining "intelligent entrepreneurship" and "talent management" is a necessary step in improving both terms. Value of human capital, or the chance for an individual to make use of their inherent intelligence, is at the heart of intelligent business. According to studies, the best course of action for national economies is to adopt open innovation models. In order to create and efficiently apply intelligent potential—which assures the expansion of the national economy—it is necessary to enhance the efficacy of scientific, educational, and innovative systems. The groundwork for entrepreneurial intelligence has been laid in view of the present status of the digital revolution in the economy.

***Keywords*—Support Vector Machine (SVM), Entrepreneurial Success, Digital Economy.**

I. Introduction

Since an entrepreneur's expectations are likely to be more balanced between realistic and aspirational compared to other managers at the same organization, their desires and ambitions, rather than strict strategic goals, can direct their actions. The characteristics of an entrepreneur include seeing possibilities and turning good ideas into reality. This action can be carried out by an individual or a small group and usually takes initiative, persistence, imagination, and a series of steps. Being an entrepreneur comes naturally to certain people[1]. Things associated with running a business has a major impact on long-term environmental changes. It plays a key role in differentiating oneself from the competitors. This has led to the transformation of promoting an entrepreneurial mindset into a primary objective of business owners, notwithstanding the fact that method is only slightly improved due to the society's group dynamics. Starting a business is a thrilling, risky, and knowledge and success that calls for specific attributes. Surely it's asserted that the presence of humans throughout the conceptualization, design, investigation into maintenance and expansion is necessary to acquire a more thorough understanding of entrepreneurial behavior. Not only in industrialized countries, but also in emerging markets, women entrepreneurs are being recognized for their potential to alleviate poverty, boost economic growth, and challenge established gender norms[2]. In so-called "emerging countries", women's entrepreneurship is both lauded and restricted due to the fact that it challenges traditional gender roles, despite the fact that this practice has been shown to help alleviate poverty. Research from a variety of sources indicates that female entrepreneurs in developing economies of Asia, Africa, and the Middle East encounter greater societal and cultural barriers than their male colleagues in developed economies.For female entrepreneurs to thrive, researchers say that less domestic work for women is a must. This is especially true in patriarchal developing-world societies where women are part of the "sandwich generation," meaning they are responsible for caring for children, the elderly, and the house.Entrepreneurship has recently come to the forefront of sustainability discussions as academics throughout the world focus on the economic and social dimensions of the issue[3]. Consequently, entrepreneurship is thought to be crucial for generating wealth, driving economic growth and advancement, reducing poverty and unemployment, increasing living standards, and improving people's well-being. Rather than quantity, quality entrepreneurship—defined as entrepreneurial efforts that are productive, imaginative, and opportunity-driven—is what is necessary to make a positive contribution to sustainable development. There is a dearth of research that examines how entrepreneurs may address the social, economic, and environmental issues of sustainable development simultaneously, despite the increasing agreement in the entrepreneurship literature that entrepreneurship can assist with all three.Since the turn of the last decade, entrepreneurs have felt the full force of digitalization's effects on the economy and society, which has paved the way for what will be known as the Fourth Industrial Revolution. Theoretical and practical considerations of digital entrepreneurship have so increased in recent years. The European Commission considers this style of entrepreneurship to be "the application of innovative digital technologies to the transformation of both established and emerging businesses".

II. Literature Survey

The ubiquitous nature of digital technologies nowadays enables the rapid development of products and services. This tendency is frequently described by the words "digitization" and "digital innovation" [4]. Digital innovation refers to the process of creating new goods and services via the use of digital technologies. This is why a new breed of entrepreneur known as a "digital entrepreneur" [5] and an approach to business known as "digital entrepreneurship" have evolved.When people rely heavily on digital technology to build and deliver services[6], a new type of entrepreneurship called "digital entrepreneurship" develops. Digital venturing is different from traditional venturing, according to the research [7].Artificial intelligence and data analytics (AIDA) have seen a marked increase in venture capital funding, setting these digital enterprises apart. The current wave of AI is widely believed to be going to trigger massive changes in both society and companies, with far-reaching effects [8]. The innovative AI-based business models and day-to-day operations of many successful organizations have already incorporated AI.Data scientists in the area of machine learning (ML) utilize complex methods to train computers to perform new tasks autonomously[9]. In spite of the fact that ML is a branch of AI, the two are distinct. Artificial intelligence (AI) is a much broader word that describes systems that are able to learn and solve issues. A result is that AI systems and programs can learn from their mistakes and accomplish jobs with human-level intelligence (OECD)[10].Deep learning (DL) is a popular supervised learning method used for feature extractionsalvaged from images and other complex, multi-dimensional datasets[11]. As a user begins to input into the search field, Google uses DL to suggest the next word or terms to include in the query. Computers outperform human brains in terms of efficiency, accuracy, and lack of bias when DL makes use of so-called (artificial) neural networks[12]. Neural networks are highly effective in extracting patterns from (extremely) non-linear processes. Below, we'll explain how the model behind the DL approach determines whether a neural network is supervised or unsupervised learning[13]. An early instance of unsupervised learning was the use of a neural network for grouping.Using a so-called self-organizing map (SOM) technique, this paper investigates the association between firm success and survival and company size. Using data from the National Survey of Small Business Finances (NSSBF), [14]classify small businesses (defined as those with less than 500 employees) into different groups based on size, ownership, and other firm attributes. The term "intelligent entrepreneurship" is defined as a subset of entrepreneurship that is carried out by highly intelligent individuals in that context[15]. They create innovative products with a social mission because they are driven by ideals of ethics, a thirst for spiritual wisdom, and a desire to better themselves [16]. Research on smart entrepreneurship is being prominently conducted at the University of Texas at Austin. The Texas school of thought holds that intellectual institutions, with their wealth of knowledge and resources, are best suited to encourage critical thinking; as a result, they often feature prominent scientists or other thinkers.We should give serious thought to studies that further the concept of digital entrepreneurship [17]. Their investigation yielded accurate ratings using Support Vector Machine (SVM) and Erratic Woods approaches employing data acquired from Chinese enterprises[18]. They used a mountain of company data to train machine learning models including neural networks and tree-based models, which improved forecasts. With the help of machine learning, researchers [19]investigated the potential worth of social network data by spotting patterns that could indicate a company's imminent demise. This research expands the usefulness of predictive analytics for entrepreneurs by including intangibles like social ties[20].Most of the work involved in starting a new business is done by these entrepreneurs using digital tools and the Internet. Despite the trend's obvious significance, there is a dearth of literature on the ways in which new technologies are transforming the entire entrepreneurial process, especially in relation to the regulatory environment[21]. A more formal explanation of the community or ecosystem component is necessary to better understand how digital technologies may affect the features and interactions of actors in the entrepreneurial process of locating resources and partners. Consumers and intermediaries have been largely ignored in the entrepreneurial literature when discussing the impact of digital technology.

III. METHODOLOGY

The digital economy's effect is spreading across several economic and social domains, which is having an impact on urban entrepreneurial growth. To better understand the impact of the digital economy on entrepreneurial activity and how it varies between cities, this study delves into the data. Combining statistics on registered enterprises in the commercial and industrial sectors with panel data obtained from cities between 2011 and 2020, we achieve this goal. Also, because the digital economy has grown at an exponential rate, the paper explores new digital risks and provides answers to these problems.

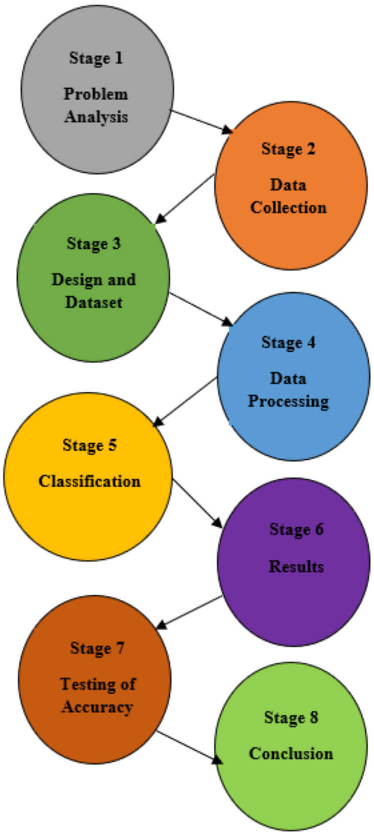

Fig. 1. Research Process Flow Diagram

The Figure 1 shows an eight-step procedure for creating a solution, most probably for a system that detects fraud. The first step is to analyze the problem in order to determine what is needed. Gathering pertinent information for analysis is the second stage of data collecting. The third stage is all about getting the dataset ready and building the model[22]. In the fourth stage, the data is prepared for analysis by processing it.Classification of models, review of results, testing of accuracy, and drawing conclusions are all part of stages 5–8.There is a logical progression from one step to the next that leads to a solid result.

A. Stratup Process

The founders of a startup are said to have achieved success when they get a substantial amount of money through an IPO or merger and acquisition (M&A). A company is considered unsuccessful if it closes its doors for good. A two-pronged strategy is the standard way that a startup's success is described. The two main ways for a company to make its shares available to the public are through an initial public offering (IPO) or through a merger or acquisition. Investors can get their hands on cash instead of waiting for the corporation to pay them for their shares. This method is often referred to as an exit strategy. Companies frequently use mergers as a means of reorganisation. Mergers and acquisitions include merging two or more businesses into one, sometimes with a different name, with the goal of increasing sales and profits. Companies that aren't tech-related but are similarly sized and prestigious often employ this strategy. Mergers and acquisitions (M&As) are fundamental in the technology industry for the rapid expansion of R&D capabilities and the acquisition of state-of-the-art technologies[23]. When one business buys out another, it usually ends up bringing the acquired company to its knees. Acquisitions occur when one entity buys a majority interest in another.
It is critical to define success in order to predict how a startup will do. They found that a startup's public standing significantly impacts a venture capital firm’s investment choice, making it an important success factor. In this proposed approach to utilised initial public offerings (IPOs) to show that VC investments in startups are heavily influenced by these events. Since all relevant information is readily available during an initial public offering (IPO), this is the most important factor in determining success.As mentioned before, a successful IPO shows that stock market investors find a company interesting. Companies who are able to pull off a successful IPO have a good chance of making it in the long run. It follows that an IPO is a measure of a company's success.

B. Preprocessing

1) Data Cleaning:

Data preparation is a crucial step in the data mining process. Firms, funding, acquisitions, and other datasets are brought together and cleaned up in this study. When cleaning data, it's common practice to look for and either remove or impute outliers, remove duplicate values, determine the item's significance, and replace missing values.The models rely heavily on data cleaning. The programmatic creation of PySpark RDD and DataFrame was made possible by Spark Session. This is useful because it allows you to conduct queries to retrieve data and receive the result as a DataFrame.Using spark, we have created data frames with defined labels after deleting rows with null or missing data.It is possible to create certain visualizations once the final dataset has been curated[24]. All of these are displayed in Figure 2. In this dataset, the'status' column represents the desired variable. Startups that have been purchased are given a value of 1. No value has been allocated to any of the other enterprises. Only fifteen percent of the enterprises were bought out.

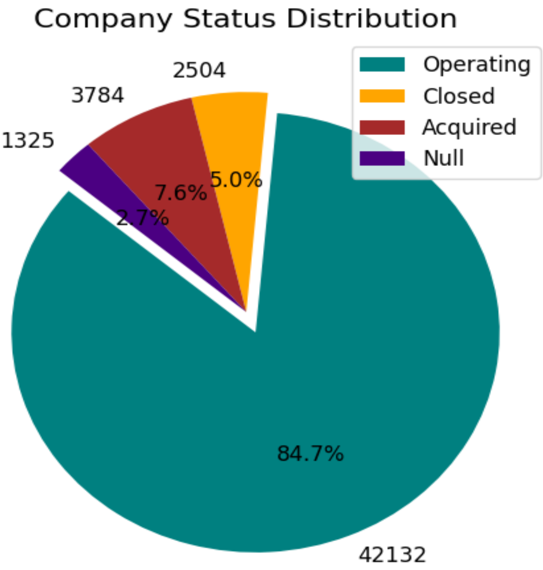

Fig. 2. Target Variable Distribution

Following the partitioning of the dataset into the training and testing sets, then constructed a vector assembler utilizing the features for the modelling process.

C. Feature Selection

Selecting relevant features for prediction purposes while discarding irrelevant or unnecessary ones is the essence of feature selection. Using feature selection approaches can drastically cut down on computing time while also improving assessment metrics like accuracy. Incorporating irrelevant details will make the research less reliable. It used the varimp() technique to identify the important model variables. Since feature selection and modelling are done concurrently in the proposed approach the wrapper technique is used to identify important variables. Environmental preservation, healthcare, weather forecasting, and economics are just a few of the several fields that benefit from feature selection. The model's reliance on data for feature and variable importance evaluation in a function determines the outcome. The ability to include the correlation structure among predictors into the relevance calculation and the close association with modelling performance are two of the most important benefits of using a model-based approach, among many others. The importance is computed, as we can see. Each class will be given its own unique significant variable based on the predictors. Then, we bring all the relevant measures up to a maximum of 100 by rescaling them. Use the varimp() method to determine the importance of each aspect thereafter. It is necessary to exclude all characteristics from the dataset in order to demonstrate varimp's effectiveness and efficiency in finding important features. Consequently, it will affect processing time, which could result in better accuracy and more features related to high-dimensional data.

D. Machine Learning Methods for Financial Fraud Detection

1) LR

Overfitting occurs in logistic regression algorithms when coefficient values are very high. In order to minimize the algorithm's cost function, the coefficients are modified at each training step. When doing logistic regression, we utilized the mean squared error (MSE) as the cost function. To prevent models from overfitting, regularization adds a coefficient-value-dependent element to the cost function. It is possible that the regularization term (L1 or Lasso regularization) is proportional to the total magnitude of the coefficients.

2) SVM

SVM is a linear classifier, just as logistic regression. In order to distinguish between categories, the algorithm searches for the best decision hyperplane. Decision function regularization is controlled by the *D* parameter of the SVM algorithm. As the degree of regularization increases, its value decreases. With a lower *D*, the classifier's decision function is forced to have a higher margin and a simpler decision surface. Underfitting the data could occur as a result of this. An improved model's ability to accurately categorize all training samples is correlated with a greater value of the D parameter[25]. Overfitting the training data and bad generalization on the test set could be unintended consequences of this. By including specialized functions known as kernels, SVM can be transformed into a non-linear classifier. A radial basis function kernel is one of them that is utilized in this investigation. The variable β is in charge of regulating its actions. A decision surface based on nearby examples is generated by the model when β is high. When β is small, events that are farther away can nevertheless affect the decision surface.

3) XGBoost

The XGBoost algorithm with CART served as the basis for our model. It decides to change the number of estimators in order to fine-tune the ensemble. It is reasonable to assume that more trees mean more exploration possibilities, given that each tree in the ensemble uses just a subset of features. The ratio of employed features to total features can be adjusted with the colsamplebytree option.It may control the maximum number of tree layers by altering the maximum depth. Trees with increasing depth tend to overfit the data more frequently. Through the use of the minimal child weight parameter, one may ascertain the minimum weight an instance must have in order to be split. By halting tree formation earlier, a higher number could prevent overfitting. For the split decision, the gamma parameter is another modifiable variable. In order to minimize losses, it determines the absolute minimum. The learning rate parameter controls the impact of following boosting stages to prevent overfitting.When compared to other popular algorithms, XGBoost offers more options for fine-tuning. Were are unable to do an exhaustive grid search of all possible combinations due to computational constraints. It is feasible to use the randomized search approach to evaluate some of the potential combinations. While this method can't guarantee finding the perfect parameters, it is thought to find models that might be as good as the ones found by a grid search.

4) DT

A decision tree is a kind of flowchart that resembles a tree structure; it provides predictions from a series of feature-based splits. The decision-making process begins at the root node and ends at the leaf nodes. There are two primary classes in the algorithm: one that contains the algorithm itself and another that defines a node and is used as a helper.

5) RF

Using a statistical sampling technique, Random Forests train multiple trees simultaneously. Consequently, there is less overfitting and the model becomes more robust. The mode of each tree's output is used to assign the final class of an instance. This method can handle a large number of input variables and produce accurate and resilient classification.This was useful for managing our dataset, which contained severely skewed distributions of classes. The model we have developed makes use of thirty trees. The same was also tested with twenty-five models.Accuracy was unaffected, although the AUC was somewhat different.

6) GB

For complicated and huge datasets in particular, gradient boosting stands out as a fast and accurate prediction method. All of the data points were given identical weights by the algorithm after it began by creating a decision stump. After that, it boosted the weights of all the incorrectly categorized points while decreasing them for the easily classified ones. For these weighted pieces of information, a fresh decision stump is created. The basic premise is that this will help the first stump make more accurate forecasts. Since the algorithm built the trees one by one, it was able to fix mistakes created by previously trained trees.

7) MLP

A multi-layer perceptron is another term for a fully connected multi-layer. It consists of an input layer, two hidden layers, and an output layer. The calculation of MLP is made up of hidden layers that are located between the input and output layers. The number of layers is completely up to you. Data flows forward from the input layer to the output layer, similar to a feed-forward network. The MLP neurons are trained using the backpropagation approach. In our research, we took into account multiple situations with varying numbers of hidden layers and 30 neurons. We discovered the optimal level of accuracy when using the greatest number of hidden layers.

IV. RESULTS AND DISCUSSION

The digital economy's effect is spreading across several economic and social domains, which is having an impact on urban entrepreneurial growth. To better understand the impact of the digital economy on entrepreneurial activity and how it varies between cities, this study delves into the data. Combining statistics on registered enterprises in the commercial and industrial sectors with panel data obtained from cities between 2011 and 2020, we achieve this goal. Also, because the digital economy has grown at an exponential rate, the paper explores new digital risks and provides answers to these problems.

TABLE I. TARGET DATA FROM THE QUESTIONNAIRE(%)

Profile	Information	Frequency	Percentage
Gender	Women	45	45%
	Men	55	55%
Age	15-25	10	10%
	21-25	25	25%
	26-30	20	20%
	31>	45	45%
Education	Bachelor	50	50%
	High School	25	25%
	Middle School	15	15%
	No education	10	10%
Machine Learning-Based Success Prediction for Digital Economy Entrepreneurs	Is the Future of the Digital Economy Predicted by Machine Learning	40	40%
	Make it easier for digital economy startups to succeed	30	30%
	Reliable Security System	10	10%
	Improve Performance and Efficacy	20	20%

Table 1 presents demographic and thematic data on digital economy entrepreneurs, broken down by gender, age, education level, and areas of interest in machine learning for digital economy success. The gender distribution is slightly male (55%), with a varied age distribution (45% of participants over 31), and the most common educational attainment level is a bachelor's degree (50%), followed by high school (25%). Important areas of interest include the role of machine learning in the digital economy's future and how to support startups to be successful.

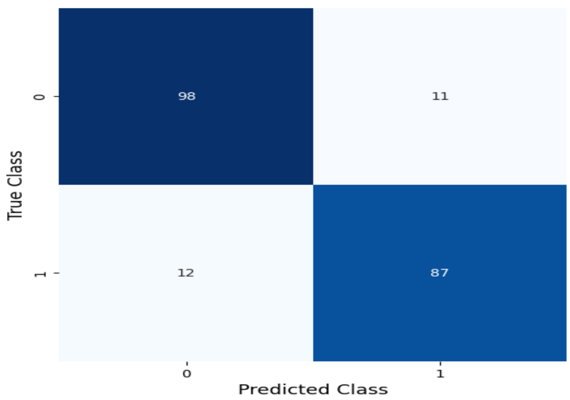

Fig. 3. Confusion Matrix for XGBoost Model

To evaluate a classification model's performance, as shown in Fig. 3, one uses the confusion matrix. This matrix indicates the model's accuracy in classifying the data. The four parts that make up a confusion matrix are TP, TN, FP, and FN standing for True Positive and False Negative, respectively. Results for this case come out to 94%.

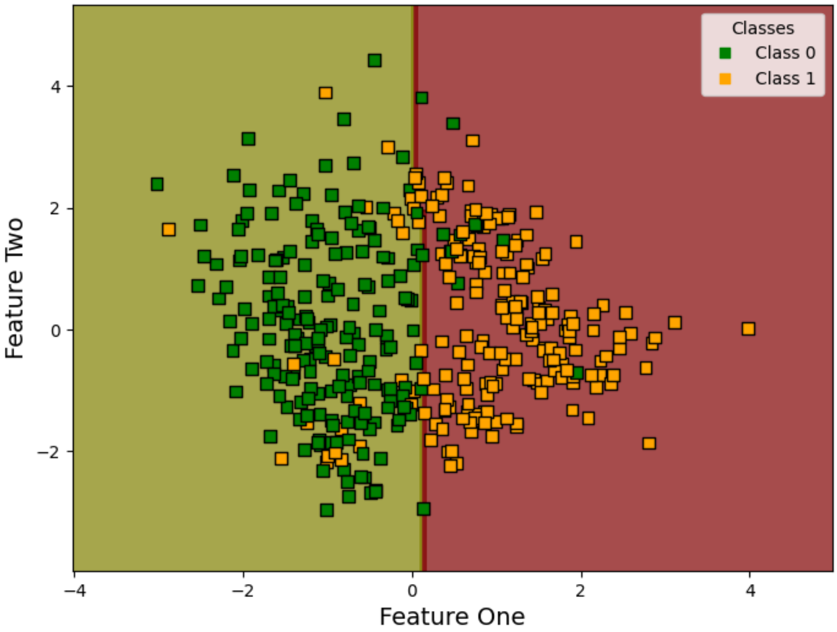

Fig. 4. The Model Evaluation

Figure 4 shows that the model is able to forecast the majority of successful startup data (green dots), but it also predicts the success of some failed startups (orange dots). This is because the dataset is imbalanced in the "status" column, which has more successful startups than unsuccessful ones.

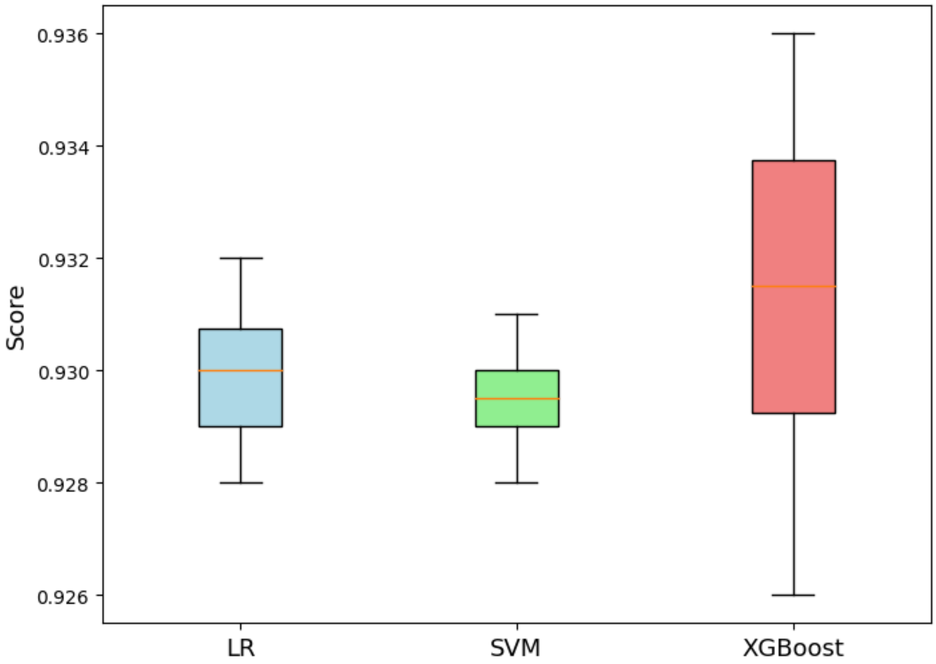

Fig. 5. Accuracy for LR, SVM and XGBoost

With very high overall accuracy, each of the machine learning algorithms that were examined was clearly a strong competitor. Figure 5 shows that, as predicted, XGBoost has the best accuracy and variance. For the present learning problem (with balanced classes), accuracy—the total of true positives and true negatives divided by the total number of observations—is a good and quick metric to pre-evaluate an algorithm's performance. The linear separation in the feature space and the excellent correlation between the dataset's characteristics allowed SVM (with a linear kernel) and LR to achieve very high overall classification accuracy.

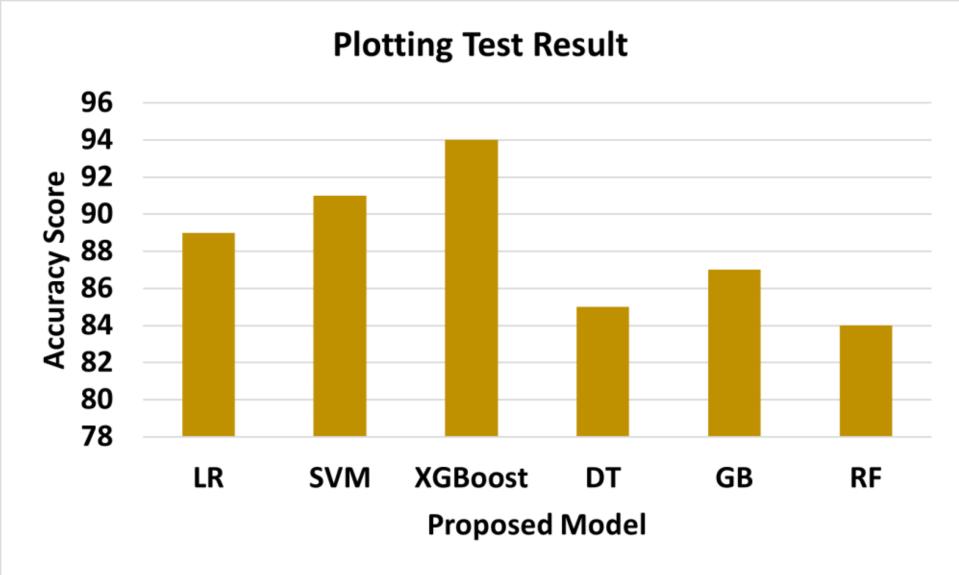

Fig. 6. Accuracy Comparison of Various Models

Figure 6 displays the results of accuracy for various methods in the classification category.

V. Conclusion and Future Directions

Two essential parts of good intellectual property management (IPM) that can improve a company's commercialization and entrepreneurial endeavors are keeping a competitive advantage and supervising outbound open innovation (OI). Consequently, the study's objectives were to gain a better understanding of the ways in which intellectual property management (IPM) can assist SMEs in enhancing their commercialization performance (CP) and entrepreneurial performance (EP) through open innovation (OI), and to determine the impact of IP protection on the development of digital economies and entrepreneurial endeavors in particular geographical areas.We achieved a maximum accuracy of 94.38% while training the model with XGBoost to forecast the digital economy's success for entrepreneurs.

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